A Semi-automatic Framework for Pattern Mining in Chart Images of Power Grids (sui bian xie de)

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Abstract

This short example shows a contrived example on how to format the authors' information for *IJCAI–19 Proceedings* using LaTeX.

1 Introduction

Transient stability analysis (TSA) is one of the most challenging problems in power grid (PG) operation [Moulin *et al.*, 2004]. It requires analysts to take preventive and correct controls on part of the grid based on observations of the operating state, so that serious failures and blackouts can be avoided. In this paper, we refer such observations to TSA patterns, including the change of stability state, the occurrence of different faults, the propagation and the influence of faults, etc.. Considering that humans are more sensitive to visual depictions of data, visualization techniques have been applied to generate efficient chart images from numerical PG simulation data to convey quantitative information [Tufte and Graves-Morris, 2014; Wong *et al.*, 2009]. However, this raises three challenging problems. First, humans can possibly deal with hundreds of charts but can hardly analyze a data set containing thousands charts. Second, sometimes analysts can only get access to chart representations without the underlying data, for example, from report documents and simulation tools. Third, the diversity of TSA patterns makes it difficult to get a labeled dataset. Therefore, a proper solution for TSA pattern mining in unlabeled chart images of PGs is in need.

Chart images are usually perceived in a different way from natural scenes. Existing chart recognition models focus on classifying chart type and decoding visual contents. Classification models like support vector machine [Savva *et al.*, 2011] and convolutional neural networks [Poco and Heer, 2017] are used. Despite the impressing performance they achieved, they have barely been tested on large data sets containing more than 10,000 charts. A more fundamental limitation is that they only model shape features. The state of art method that includes semantic features is visual question answering models. But such models are proved incapable of answering many questions in chart images [Kafle *et al.*, 2018]. There are limited studies aiming to identify semantic patterns in an unsupervised manner, which faces two critical challenges: (i) How to define unknown patterns and assure it's semantically meaningful for PG analysts? (ii) How to identify patterns when each chart image may contain a combination of multiple patterns?

To tackle the first problem, we introduce interactive visualization techniques to allow PG experts to efficiently define patterns based on perception-level visual depictions of the original charts so that domain knowledge can be involved. As for the second one, our patterns are defined on low-dimensional representations rather than the chart itself. Visualization allows the adjustment of representations so that each defined representation corresponds to a pattern. In this way, the representation of a chart can be similar to multiple pattern representations.

In general, we propose a novel semi-automatic framework for TSA pattern mining in unlabeled chart images of smoothly-transitioned time-domain simulation data of PGs. We test our framework on one particular kind of chart, pixel map, which is one of the most commonly used type for TSA pattern analysis. As shown in Figure(Framework picture), we first train a hierarchical variational auto-encoder (VAE) to learn the representation of pixel maps, composed of a hierarchical organization of explanatory factors. The representations are then passed to a visualization system in which they are visually depicted and adjusted. Finally, defined TSA patterns can be identified in the entire data set by computing the similarity to the defined representation. For newly acquired data, TSA patterns can also be identified once its representation is got from the trained hierarchical VAE model.

This paper makes three major contributions:

- We propose a semi-automatic TSA pattern mining framework for simulated PG pixel maps, so that much labor can be released from tedious and time-consuming visual analysis works which is so far performed complete manually.
- We introduce visualization techniques to enhance representation learning and factor analysis, so that more interpretive and more semantically meaningful TSA patterns can be identified.
- We collect pixel maps of real-world PG simulation data to evaluate our method. (add: performance)

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2 Related Work

Chart Image Recognition

Variational Autoencoder Based Representation Learning. We adopt variational Autoencoder (VAE) to directly and parametrically learn the representation [Kingma and Welling, 2013; Tschannen *et al.*, 2018], which turns out to be the posterior distribution $p_\theta(z|x)$ on the latent space given an observed input x. Models such as β-VAE [Higgins *et al.*, 2016], FactorVAE [Kim and Mnih, 2018] and InfoVAE [Zhao *et al.*, 2017] disentangle x so that different variables z_i in $p_\theta(z|x)$ capture independent factors that are assumed to generate x. This assumption makes it possible to define semantic patterns (a combination of factors) by adjusting z in $p_\theta(z|x)$. However, analysts may still get confused with which z_i to be adjusted since the size and sort of z hardly reach trial level. Hierarchical VAE solves this problem by constructing a hierarchy of z so that z_i in z can be studied in a grouped manner [Gulrajani *et al.*, 2016; Sønderby *et al.*, 2016; van den Oord *et al.*, 2017]. (Add introductions to hierarchical vae if necessary.)

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